

## Robust Localization Algorithm Based on Best Length Optimization for Wireless Sensor Networks

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### Abstract

*In this paper, a robust range-free localization algorithm by realizing best hop length optimization is proposed for node localization problem in wireless sensor networks (WSNs). This algorithm is derived from classic DV-Hop method but the critical hop length between any relay nodes is accurately computed and refined in space WSNs with arbitrary network connectivity. In case of network parameters hop length between nodes can be derived without complicated computation and further optimized using Kalman filtering in which guarantees robustness even in complicated environment with random node communication range. Especially sensor fusion techniques used has well gained robustness, accuracy, scalability, and power efficiency even without accurate distance or angle measurement which is more suitable in nonlinear conditions and power limited WSNs environment. Simulation results indicate it gained high accuracy compared with DV-Hop and Centroid methods in random communication range conditions which proves it gives characteristic of high robustness. Also it needs relatively little computation time which possesses high efficiency. It can well solve localization problem with many unknown nodes in the network and results prove the theoretical analysis.*

**Keywords:** WSNs, Localization Algorithm, Robustness, Hop Length Optimization

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### 1. Introduction

Wireless sensor networks (WSNs) are composed of thousands of tiny and intelligent sensors which are responsible for their organization, configuration and working in order to provide sensing tasks assigned to them. As the development of low-cost and low power sensors, micro-processor and radio frequency circuitry for information transmission, there is a rapid development of WSNs [1], which can be deployed in large numbers and provide unprecedented opportunities for various kind of applications, such as military surveillance, environmental monitoring, habitat monitoring, and structural monitoring etc., [2-5]. There are many challenges in these broad applications.

However sensor node localization has become the most important one, namely how to localize unknown sensors with smallest number of anchors that reduces computation time, communication overheads, and energy consumption but with high localization accuracy has become a hot research topic.

One common way in the world is Global Positioning System (GPS) system. But it is not suitable in WSNs because its performance degrades drastically when receiver is in indoor or located in forest environments. Meanwhile as a result of constraints in size and power consumption, it is unfeasible to equip traditional GPS receivers for all nodes in WSNs. Only those that have the features of well flexibility, convenient maintenance and low-cost update are highly needed. Node localization is one of the important supporting technologies in WSNs.

Node location information should be included in the collected information so as to realize unknown localization process in the physical world. Until now many algorithms especially designed for WSNs environment have been proposed and can be sorted into range-based category [6], such as AoA (Angle of Arrival) measurement [7], ToA (Time of Arrival), TDoA (Time Difference of Arrival) [8, 9], and RSS (Received Signal Strength) [10, 11]. The RSS way is superior to the technologies based on TDOA, TOA and AOA [10]. The RSS-based locating

technology has the characteristics of low cost, no extra hardware requirements, easy to implement, which has been widely applied. In recent years, the sparse transformation and compressed sensing on WSNs locating research have become the academic hotspot.

The other main category is described as range-free. This one only employs distance vector exchange and network connectivity to find the distances between the non-anchor nodes and the anchor nodes to realize node localization by performing a tri-lateration or multi-lateration technique [12, 13] including DV-hop [14], DV-distance, APIT, Euclidean, Amorphous [15], Centroid and others. The differences between range-based and range-free are that range-based approaches have higher accuracy but more expensive hardware and higher power consumption are needed and range-free ones need no more complicated hardware and power consumption but with relatively low position estimation error. The parameter that determines its accuracy is derivation of hop length between two nodes.

In this paper, a robust range-free localization algorithm by realizing best hop length optimization, which is high efficient and accurate, is proposed. This algorithm is derived from classic two-dimensional DV-Hop method but the critical hop length between any relay nodes is accurately computed and refined in space WSNs with all sensors deployed randomly and arbitrary network connectivity. In case of network parameters hop length between nodes can be derived without complicated computation and further optimized using Kalman filtering in which guarantees robustness even in complicated environment with random node communication range. Especially sensor fusion techniques used in this paper has well gained robustness, accuracy, scalability, and power efficiency even without accurate distance or angle information which is more suitable in nonlinear conditions.

The contribution of this paper is as follows. A robust 3D node localization based on probability density function analysis is proposed and in this algorithm the best hop length is computed by using regional direction estimation and refined by data fusion technology with relatively low computation time and power consumption. It has a high robust localization accuracy and robustness. The communication range is not fixed but randomly changed, which makes it more suitable in complicated environments. This break through the biggest restraint in wireless sensor networks.

The rest of the paper is organized as follows. Section II gives some basic problem statement and parameter definitions. Hop length optimization with Kalman filtering are described in Section III. Section IV describes the whole localization algorithm and Section V illustrates the theoretical and simulation results. Finally, conclusions are listed in section VI.

## **2. Problem Statement and Parameter Definitions**

### **2.1. Problem Statement**

In range-free localization algorithms distance between unknown nodes and anchors is the key parameters and becomes the core procedure in the localization algorithms. Normally this distance is computed by hop length and hop counts between unknown and anchors. Once the three similar distances are obtained the unknown coordinates can be computed by multi-lateration methods.

In densely deployed WSNs, a shortest multi-hop path between any pair of the sensor nodes may be existed. By discharging one hop away from the start node, the accumulative distance is likely to be increased by one transmission range [16]. As supposed in the front all nodes have the same property, the distance between any pair of the sensors (*Start – End*) can be approximately estimated by the transmission range multiply the corresponding hop counts between them [17]. That is also the core concept of classic DV-Hop propagation algorithm.

But in some bad environment, the density of nodes is very low which is not adequate to construct a straight and shortest multi-hop path between two sensors. In this situation it is impossible for an intermediate sensor to be located close to the boundary of the last one, which makes the estimated distance is far from the true value. It means a lot of localization errors are introduced.

In order to overcome this problem how to optimize and refine the hop length between nodes become critical and determines the final localization accuracy.

## 2.2. Parameter Definitions

In the real WSNs, sensor nodes are sprinkled by low flying airplanes or unmanned ground vehicles, all of them are out of control, which makes regularity and topology of the network or the affirmatory pattern hard to be gotten. There are two kinds of nodes in them, one is called anchor node with definitely known position coordinates and the other is unknown nodes which needs to be realized. They are sprinkled together at the same time. Furthermore, all sensor nodes are assumed to be omni-directional, homogeneous and stationary to some extent, which is to say the whole network can be seen as static or regarded as a special snapshot of a mobile ad hoc sensor network. Some parameters used in this algorithm are defined as follows.

$N = (n_1, n_2, \dots, n_N)$ : Total number of sensors in 3D WSNs with  $n_i$  as the  $i$ th node.

$V = L \times L \times L$ : Localization space is a cube as the volume is  $V$  with side length  $L$ .

$\lambda = N/V$ : Node density in the localization space which subjects to 3D Poisson distribution [18] results from random deployment of sensor nodes in 3D space.

$V_0(n_i)$ : The occupied space region with  $n_i$  node as the center and communication range  $r_i$  as its radius which is a random variable up to itself. We can find  $V_0(n_i) = 4\pi r_i^3 / 3$ . In this way the space region of each node is a sphere and any node in it will be seen as its neighbor.

$N(C)$ : The number of all sensors in one sphere and obviously  $N(C) = 4\lambda\pi r_i^3 / 3$  and  $n_i$  is the center of the sphere.

$N_c$ : The number of one sensor's neighbors and it can be easily computed as  $N_c = N(C) - 1$ .

$A_i(X_i, Y_i, Z_i)$ : Anchor node  $A_i$  with  $(X_i, Y_i, Z_i)$  as its coordinate. Its coordinates are predefined or from GPS because anchors are a kind of node different from ordinary ones with high power and energy.

In the proposed algorithm the number of hop length needed dealt by Kalman filter for each time is set as 500 to realize optimization. In the model only number of anchor nodes can be changed manually, namely percentage of anchors. The total number of sensors is fixed at 200, which can well represent the real application environment. Note that percentage of anchors in the network is much smaller than that of unknown sensor nodes in the real WSN environment.

## 3. Hop Length Analysis and Optimization with Kalman Filtering

### 3.1. Best Hop Length Analysis

Suppose there is a sensor node indicated as  $S_i$  with random communication range  $r_i$ . In this way all nodes in the sphere formed by node  $S_i$  as its center and random radius  $r_i$  are the neighbors of node  $S_i$ , which is shown in Figure 1. So as shown in Figure 1 once starting node  $S_i$  is given the hop length towards end node  $E_i$  is at each hop is denoted as  $R_i$  which is also a random variable.

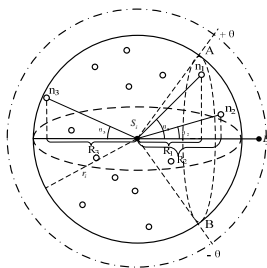


Figure 1. Formation of hop length

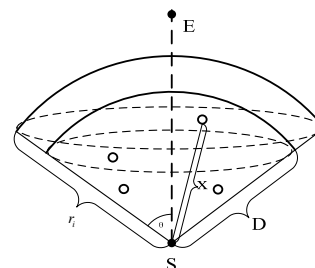


Figure 2. Best hop length computation

As analyzed before the adjacent hop may not on the straight line connected from node  $S_i$  to  $E_i$ . A neighbor sensor node  $n_j$  who located nearest its boundary should be selected as the next hop node. Just as shown in Figure 1  $R_i$  is the projection of  $r_i$  on line  $SE$ . In Figure 1 it is obvious that  $R_3 > R_1 > R_2 > R_i (i \neq 1, 2, 3)$ . However this special sensor node  $n_3$  should be neglected for its opposite direction with  $\overline{SE}$ , which means for any relay sensor node, only those neighbors whose position is closer to the ending node  $E$  than the current sensor are considered for the next hop node. Another problem is how to choose between  $n_1$  and  $n_2$ . As shown in Fig.1 both  $n_1$  and  $n_2$  are in the same space circular cone  $ASB$ . Here we call spherical space  $S$  as  $V_1$  and compute  $R_1$  and  $R_2$  as  $R_1 = r_1 \cos \theta_1$  and  $R_2 = r_2 \cos \theta_2$ . Finally we select node  $n_2$  as the next hop node for  $R_1 < R_2$ . That is because it is more close to communication range of node  $S_i$ .

As analyzed before, parameter  $\theta$  is critical because it can decide the size of space region where the best relay hop nodes locate. In order to obtain the rational  $\theta$ , we suppose there is a sensor node  $S'$  on the intersection point of  $SE$  and sphere  $S$ . In this way the next optimum hop length to node  $E$  can reach its maximum value  $r_i$ . The special intersection space region  $V_2$ , which is formed by sphere  $S$  and  $S'$ , can be a perfect estimation of the space step region for source node  $S$ . But  $V_1$  is better than  $V_2$  to be seen as the optimum space because maximum projection of sensor nodes in  $(V_2 - V_1)$  on  $SD$  is  $r_i / 2$  which has low accuracy, which makes  $\theta = \pi / 3$ . In this way optimum space hop length can be formed.

### 3.2. Overview of Kalman Filtering Algorithm

Although WSNs technologies developed very quickly, challenges associated with the scarcity of bandwidth and power in wireless communications have to be addressed. For the state-estimation problems discussed here, observations about a common state are the best hop length computed before. To perform state estimation, sensors may share these observations with each other or to form a fusion center for centralized processing. In either scenario, the communication cost in terms of bandwidth and power required to convey observations is large enough to merit attention. Also in some actual testing environment (temperature, pressure field, magnetic field, etc.), the state changes of sensor node are almost consecutive, which forms a smooth and continuous curve surface. The parameters in Kalman filtering can be performed easily.

The Kalman filtering (KF) offers an elegant, efficient and optimal solution to localization problems in WSNs when the system at hands is distributed and random measurements errors exist [19]. In the paper, the Kalman filter (KF) based approach was selected in order to reduce the effects of hop length errors between anchors and unknown nodes and to obtain property of robustness against existing errors in distance measurements. To explore this point, consider a vector state  $x(n) \in R^p$  at time  $n$  and let the  $k$ th sensor collect observations  $y_k(n) \in R^q$ . The basic linear state and observation models are:

$$\begin{cases} \mathbf{x}(n) = \mathbf{A}(n)\mathbf{x}(n-1) + \mathbf{u}(n) \\ \mathbf{y}_k(n) = \mathbf{H}_k(n)\mathbf{x}(n) + \mathbf{v}_k(n) \end{cases} \quad (1)$$

Where the driving noise vector  $\mathbf{u}(n)$  is normal Gaussian noise and uncorrelated across time with covariance matrix  $\mathbf{C}_u(n)$  while the normal observation noise  $\mathbf{v}_k(n)$  has covariance matrix  $\mathbf{C}_v(n)$  and is uncorrelated across time and sensors. With  $K$  vector observations  $\mathbf{y}_k(n)$  available, the optimum estimation of  $x(n)$  can be derived using equation 1. The rude collection of these observations and the process of these measurements, however, incur relatively high power consumption with the product of the number  $K$  of sensors in the network. The computation times that provided to Kalman filtering can be controlled by the algorithm itself by changing parameters of the network. And in this paper this value is set as 500.

#### 4. The Whole Algorithm Realization

In this part whole algorithm which realize localization for each unknown sensor node is depicted. The best hop length computation is given first and then the whole localization algorithm is described.

##### 4.1. Best Hop Length Computation

As indicated before, all sensors are deployed in 3D WSNs, subjecting to Poisson distribution with node density  $\lambda = N/V$  [18]. Then, the probability of  $m$  sensors located within a sensor  $n_i$ 's space region, namely  $V_0(n_i) = 4\pi r_i^3/3$ , can be expressed as following equation:

$$p(m, r_i) = \frac{[\lambda V_0(n_i)]^m}{m!} e^{-\lambda V_0(n_i)} = \frac{(4\lambda\pi r_i^3/3)^m}{m!} e^{-4\lambda\pi r_i^3/3} \quad (2)$$

Just as the model explained another equation can be written as  $V_1 = 2\pi r_i^3(1 - \cos\theta)/3$ . Similarly, the probability of  $m$  sensors can be located in a sphere space section between  $(-\theta, +\theta)$  of a sensor's transmission range will be as follows:

$$p(m, \theta) = \frac{(\lambda V_1)^m}{m!} e^{-\lambda V_1} = \frac{[2\pi\lambda r_i^3(1 - \cos\theta)/3]^m}{m!} e^{-2\pi\lambda r_i^3(1 - \cos\theta)/3} \quad (3)$$

Expand it to 3D space as shown in Figure 2. We suppose variable  $x$  to be the distance between  $S_i$  and its next potential forwarding sensor. It is obvious  $x$  is a random variable and the probability of  $x$  being less than  $D$  can be given as  $D$  can be obtained using following equation.

$$\begin{aligned} p(x \leq D) &= \sum_{m=0}^{\infty} p(m, \theta, r_i) p(m, \theta, D) \\ &= e^{-2\pi\lambda(1 - \cos\theta)(r_i^3 - D^3)/3} \end{aligned} \quad (4)$$

And the probability density function (PDF) can be computed by differential using the following equation.

$$\begin{aligned} f_x(D) &= \frac{d}{dD} (p(x \leq D)) \\ &= 2\pi\lambda D^2 (1 - \cos\alpha) e^{-2\pi\lambda(1 - \cos\alpha)(r_i^3 - D^3)/3} \quad (0 < \alpha < \theta) \end{aligned} \quad (5)$$

As the definition of hop length  $R_i$ , the projection on the line connecting the source and the destination nodes, we can easily get  $R = x \cos\theta$ . Further the best hop length  $O(R)$  can be computed as following:

$$O(R) = \frac{\int_0^\theta \int_0^{r_i} f_x(D) D \cos\alpha d\alpha dD}{\theta} \quad (6)$$

Finally once node density  $\lambda$  is given, we can obtain the best hop length using equation (6) for each unknown nodes.

##### 4.2. Realization of the Proposed Algorithm

The proposed localization algorithm with best hop length optimization and Kalman filtering mechanism is described explicitly in this part and some basic symbols are listed first.

$U_i$ : ID of arbitrary unknown node

$A_i$ : ID of arbitrary anchor node

$Num\_Nei\_U_i$ : Number of sensor  $U_i$ 's neighbors

$Set\_Nei\_U_i$ : Set of sensor  $U_i$ 's neighbors

$H_c$ : Hop counts to arbitrary anchor node

$H_L$ : Hop length to arbitrary anchor node

First each unknown sensor node  $U_i$  initializes itself by setting its own  $Num\_Nei\_U_i = 0$  and  $Set\_Nei\_U_i = \{0\}$ . And then they monitor information packages from any anchor nodes to construct the connectivity of the network. Equation (6) is used for each unknown to compute best hop length. Then each anchor node  $A_i$  floods information packet over the whole network, which includes ID of anchor node  $A_i$ , hop counts  $H_c$  to corresponding anchor node  $A_i$  and hop length  $H_L$  to corresponding anchor node  $A_i$ . As indicated  $Num\_Nei\_U_i = 0$  and  $Set\_Nei\_U_i = \{0\}$ . Once unknown node receives any anchor's packets it checks if it is from a new anchor. If so, records the ID and renews  $H_c$  and  $H_L$  by using  $H_c = H_c + 1$  and  $H_L = H_L + O(R)$ . Otherwise  $H_c = H_c + 1$  and  $H_c$  are compared. If the former is smaller, renew  $H_c$  or discard the packet. After all of above is finished, unknown node rebroadcasts the packet. The whole process ends when anchor node receives packet from all other anchors. For each time 500 computed best hop length to anchor nodes for each node are stored and dealt using Kalman filter model to perfect the collected distance data to anchor nodes. The most accurate distance estimation can be derived by refining those distance estimations. Finally all the coordinates of all unknown nodes can be derived by other mechanisms, such as tri-angle method and multi-lateration algorithm.

## 5. Simulation Validation

The simulation is made in the MATLAB (R2008a) software and some assumptions we made are listed first in the following.

- The whole sensor network is made up of total 200 nodes and the 3D sensing area is  $100 \times 100 \times 100 m^3$ .
- The percentage of anchors can be changed manually and communication range is a random variable.
- The observation frequency of Kalman filtering is set as 500.

The performance indexes are localization error, root mean square error (RMSE) and the localization time compared with classic DV-Hop and Centroid methods.

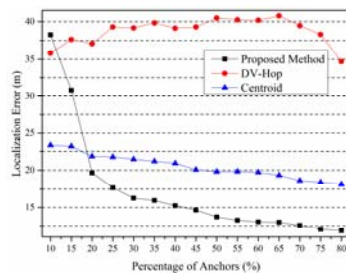


Figure 3. Error comparisons

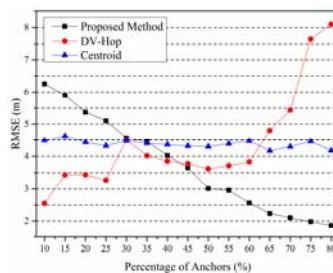


Figure 4. RMSE comparisons

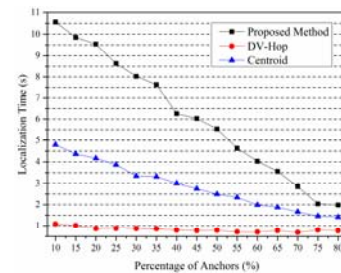


Figure 5. Time comparisons

In the figure above localization errors of DV-Hop, Centroid and proposed method in this paper are given. The percentage of anchors is changed from 10% to 80%. Of cause too high percentage is unrealistic in actual WSN environment. Here we just explore the performance deeply in the simulation process. The error of DV-Hop stays at a high level no matter how anchor nodes are changed. Centroid is much better than DV-Hop. The accuracy of Centroid is always higher in any situation. The Centroid is almost 100% better at the most. Also Centroid is more stable than DV-Hop. There is no fluctuation of Centroid which is much different from DV-

Hop. Its localization error changes between 17.5m and 22.5m, which is much better than DV-Hop.

However when percentage of anchors is lower than 10%, the error of our proposed method is the largest. That is because too few anchors cannot help unknown nodes to compute best hop length and introduces lots of accumulated errors. But as the number of anchors increase, its accuracy is getting higher and higher. Just when the value is 20% it becomes the best of the three and it is stable compared with the others. And its error goes on being smaller and smaller. The smallest error of the proposed one is less than 10m, which is only 5% of the side length. The best value of the proposed method is 69.7% and 34.8% better compared with DV-Hop and Centroid.

Figure 4 gives the root mean square error (RMSE) comparisons of the three. DV-Hop presents an upward trend and Centroid keeps stable. The RMSE of Centroid keeps around 4.5m and there are almost no big fluctuations as percentage of anchors changes. DV-Hop fluctuate fiercely and the largest value can reach 8m, which means the environment makes big effects on DV-Hop and sometimes cannot localize itself. Our proposed is definitely the best. It gives a downward trend and better localization performance. The best is less than 2m.

Figure 4 and Figure 5 both depicts accuracy problems of the three. In all proposed method outperforms both the other two. It not only has the least localization error but also has the best RMSE. There is another important index need to be analyzed, namely efficiency. Here we compute the localization time that the three needed, as shown in Figure 5.

It is easy to understand when fewer nodes need to be localized less time will be needed. As shown in Figure 5 the three all give downward trend as unknown nodes get smaller. DV-Hop and Centroid are so simple that they need no complicated computation which makes them need less localization time. DV-Hop needs least time no matter how many nodes need to be localized. It is decided by the algorithm itself. There is no much computation and just one computation process which save a lot of time. Centroid is worse than DV-Hop, because it has to compute the center of some anchors many times. So it consumes more time than DV-Hop. These two algorithms are both fast localization algorithms for their simplicities. And they need less time than most of other proposed algorithms now.

But to some extent our proposed one is the most complex of the three so it needs more computation time with highest accuracy. It not only has localization process but also there is a hop length optimization step and filtering process, which is unavoidable for time consumption. But compared with the other two the time cost is in an accepted range. The worst is about 10.5 seconds which is not a large value. But it realize 90% of all sensor' localization demand and accuracy is much better than the other two. So it is valuable to obtain much higher accuracy but give up some time performances in the actual use, which is very meaningful.

## 6. Conclusion

Precise locating target is a precondition for the practice of wireless sensor network, which is connected to the quality of network data collection, data query, data storage, and other applications. The range-free hop length optimization localization algorithm for 3D-WSNs localize the sensors with the help of anchors. In this paper we propose a robust range-free localization algorithm by realizing best hop length optimization, which is high efficient and accuracy. This algorithm is derived from classic two-dimensional DV-Hop method but the critical hop length between any relay nodes is accurately computed and refined with all sensors deployed randomly and arbitrary network connectivity. In case of network parameters hop length between nodes can be derived without complicated computation and further optimized using Kalman filtering in which guarantees robustness even in complicated environment with random node communication range. The results of the simulation experiment indicate that the algorithm proposed in the paper is better than the traditional method in terms of the localization error and energy efficiency.

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